CS 1571 Introduction to AI
Lecture 24b

Learning

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Machine Learning

- The field of **machine learning** studies the design of computer programs (agents) capable of learning from past experience or adapting to changes in the environment
- The need for building agents capable of learning is everywhere
  - Predictions in medicine, text classification, speech recognition, image/text retrieval, commercial software
- Machine learning is not only the deduction but induction of rules from examples that facilitate prediction and decision making

Learning

Learning process:

Learner (a computer program) processes data ***D*** representing past experiences and tries to either to develop an appropriate response to future data, or describe in some meaningful way the data seen

Example:

Learner sees a set of patient cases (patient records) with corresponding diagnoses. It can either try:

- to predict the presence of a disease for future patients
- describe the dependencies between diseases, symptoms

Types of learning

- **Supervised learning**
  - Learning mapping between inputs x and desired outputs y
  - Teacher gives me y's for the learning purposes
- **Unsupervised learning**
  - Learning relations between data components
  - No specific outputs given by a teacher
- **Reinforcement learning**
  - Learning mapping between inputs x and desired outputs y
  - Critic does not give me y's but instead a signal (reinforcement) of how good my answer was
- **Other types of learning:**
  - **explanation-based learning, etc.**

Supervised learning

Data: $D = \{d_1, d_2, .., d_n\}$ **a set of *n* examples**

$d_i = < \mathbf{x}_i, y_i >$

$\mathbf{x}_i$ is input vector, and y is desired output (given by a teacher)

Objective: learn the mapping $f : X \rightarrow Y$

s.t. $y_i \approx f(x_i)$ for all $i = 1,.., n$

Two types of problems:

- **Regression:** X discrete or continuous $\rightarrow$
  Y is **continuous**
- **Classification:** X discrete or continuous $\rightarrow$
  Y is **discrete**

Supervised learning examples

- **Regression:** Y is **continuous**

Debt/equity
Earnings
Future product orders

$\longrightarrow$ company stock price

- **Classification:** Y is **discrete**

```
# ######
      ##
     ##
  ######
      ###
#      ##
# ##   ##
  #######
```

$\longrightarrow$ Label "3"

Handwritten digit (array of 0,1s)

Unsupervised learning

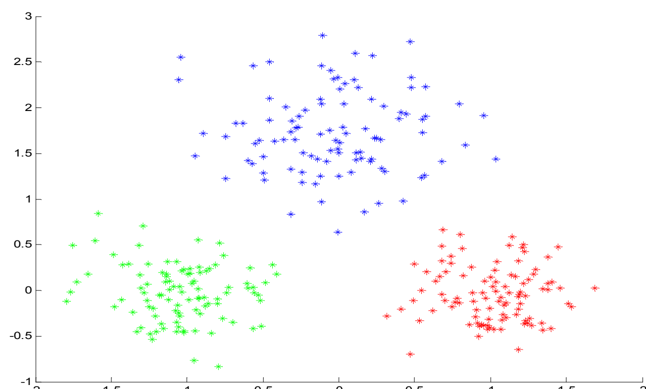
- **Data:** $D = \{d_1, d_2, .., d_n\}$
  $d_i = \mathbf{x}_i$ vector of values
  No target value (output) y

- **Objective:**
  – learn relations between samples, components of samples

Types of problems:
- **Clustering**
  Group together "similar" examples, e.g. patient cases
- **Density estimation**
  – Model probabilistically the population of samples

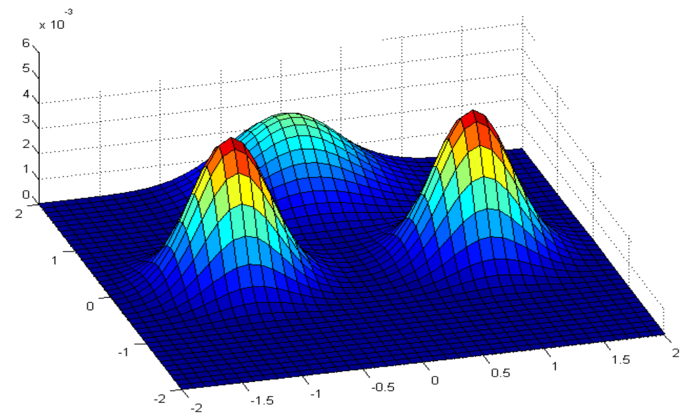
Unsupervised learning example.

- **Density estimation.** We want to build the probability model of a population from which we draw samples $d_i = \mathbf{x}_i$



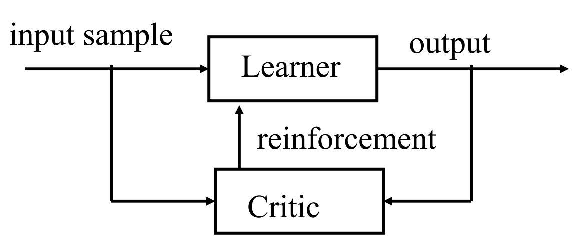
Unsupervised learning. Density estimation

- A probability density of a point in the two dimensional space
  - Model used here: Mixture of Gaussians



Reinforcement learning

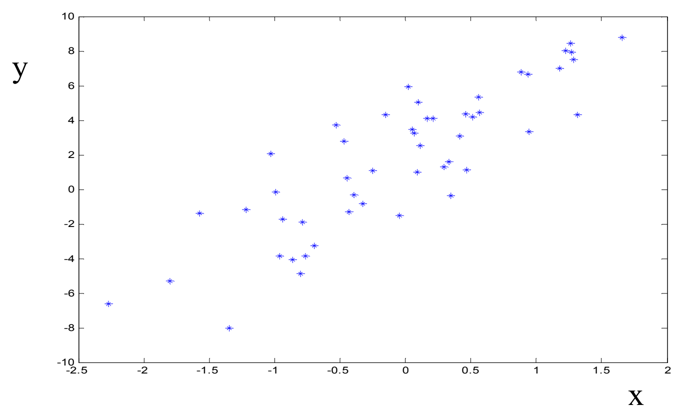
- We want to learn: $f : X \rightarrow Y$
- We see samples of **x** but not y
- Instead of y we get a feedback (reinforcement) from a **critic** about how good our output was



- The goal is to select output that leads to the best reinforcement

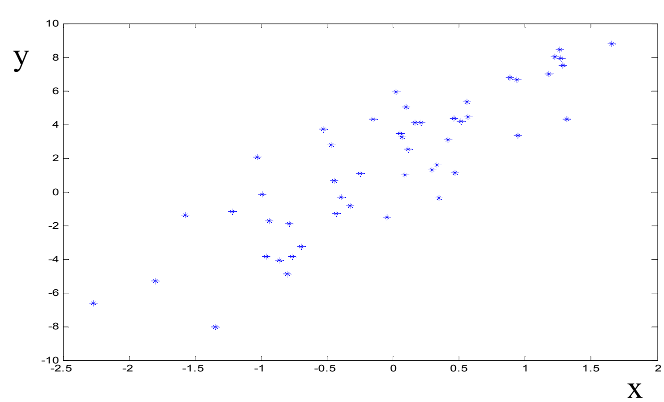
Learning

- Assume we see examples of pairs (**x** , *y*) and we want to learn the mapping $f : X \rightarrow Y$ to predict future ys for values of **x**
- We get the data what should we do?



Learning bias

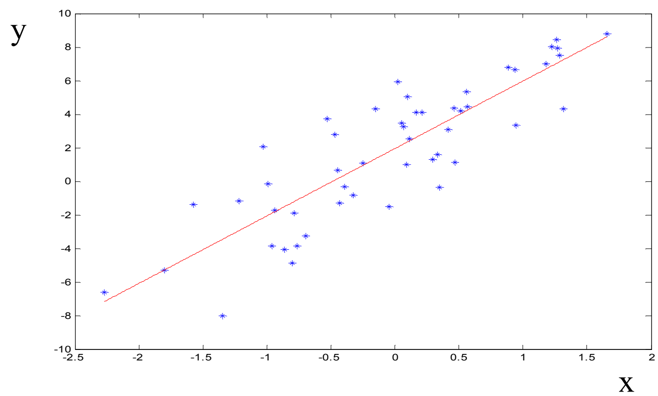
- **Problem:** many possible functions $f : X \rightarrow Y$ exists for representing the mapping between **x** and y
- Which one to choose? Many examples still unseen!



Learning bias

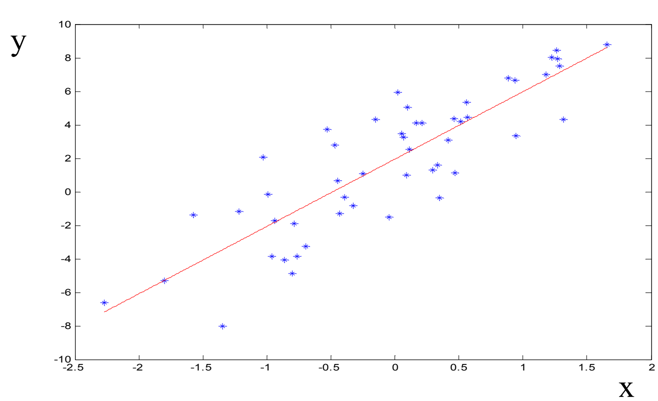
- Problem is easier when we make an assumption about the model, say, $f(x) = ax + b + \varepsilon$

  $\varepsilon = N(0, \sigma)$ - random (normally distributed) noise
- Restriction to a linear model is an example of the learning bias



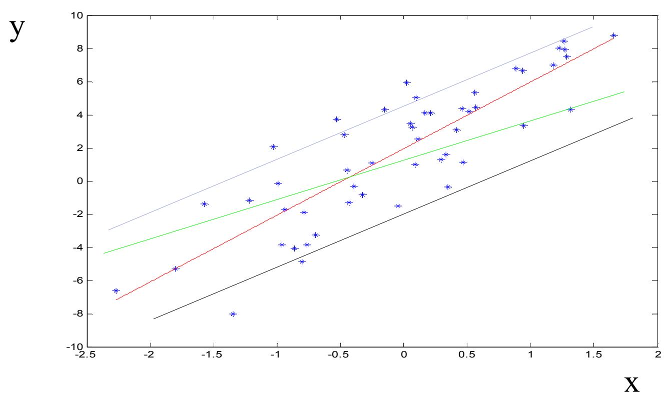
Learning bias

- **Bias** provides the learner with some basis for choosing among possible representations of the function.
- **Forms of bias:** constraints, restrictions, model preferences
- **Important: There is no learning without a bias!**



Learning bias

- Choosing a parametric model or a set of models is not enough
  Still too many functions $f(x) = ax + b + \varepsilon \quad \varepsilon = N(0, \sigma)$
  - One for every pair of parameters *a, b*



Fitting the data to the model

- We are interested in finding the **best set** of model parameters

Objective: Find the set of parameters that:

- reduce the misfit between what model suggests and what data say
- Or, (in other words) that explain the data the best

Error function:

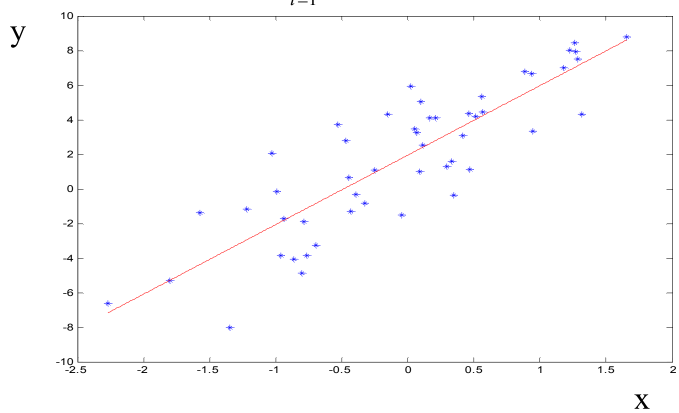
Measure of misfit between the data and the model

- Examples of error functions:
  - Mean square error $\frac{1}{n}\sum_{i=1}^{n}(y_i - f(x_i))^2$
  - Misclassification error

Average # of misclassified cases $y_i \neq f(x_i)$

Fitting the data to the model

- **Linear regression**
  - Least squares fit with the linear model
  - minimizes $\frac{1}{n}\sum_{i=1}^{n}(y_i - f(x_i))^2$



Typical learning

Three basic steps:

- **Select a model** or a set of models (with parameters)

  E.g. $y = ax + b + \varepsilon \qquad \varepsilon = N(0,\sigma)$
- **Select the error function** to be optimized

  E.g. $\frac{1}{n}\sum_{i=1}^{n}(y_i - f(x_i))^2$
- **Find the set of parameters optimizing the error function**
  - The model and parameters with the smallest error represent the best fit of the model to the data

But there are problems one must be careful about …